Online Short-Term Forecast of System Heat Load in District Heating Networks

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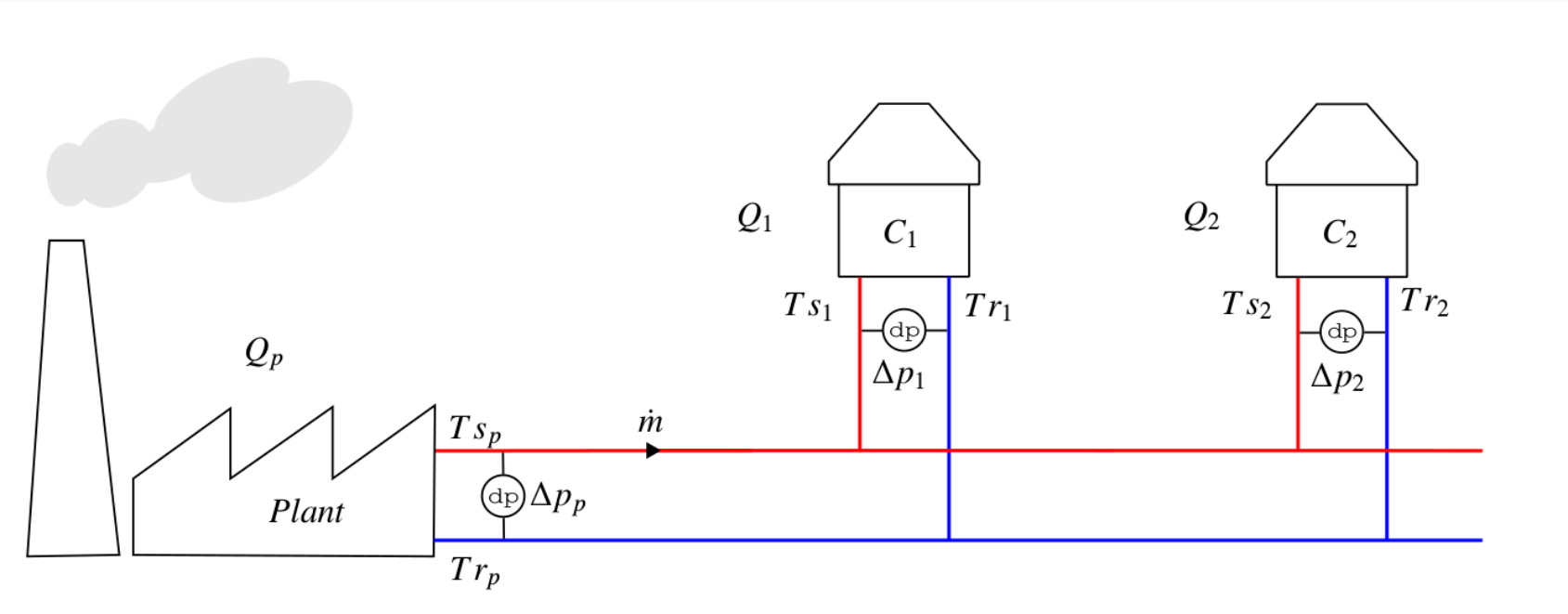
Introduction

Background and goal

Motivation Predicting energy use is essential for effective operation planning

Background and goal



Background and goal

Motivation Predicting energy use is essential for effective operation planning

Goal To accurately predict Heat Load requirement for a Housing network

Parsing the title

Online Short-Term Forecast of System Heat Load in District Heating Networks

Parsing the title

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- Variable values are available each step of the model

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- Variable values are available each step of the model
- 12 – 24h ahead

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- Total heat load in central plant

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- Variable values are available each step of the model
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- Total heat load in central plant
- Central plant distributes heat to network

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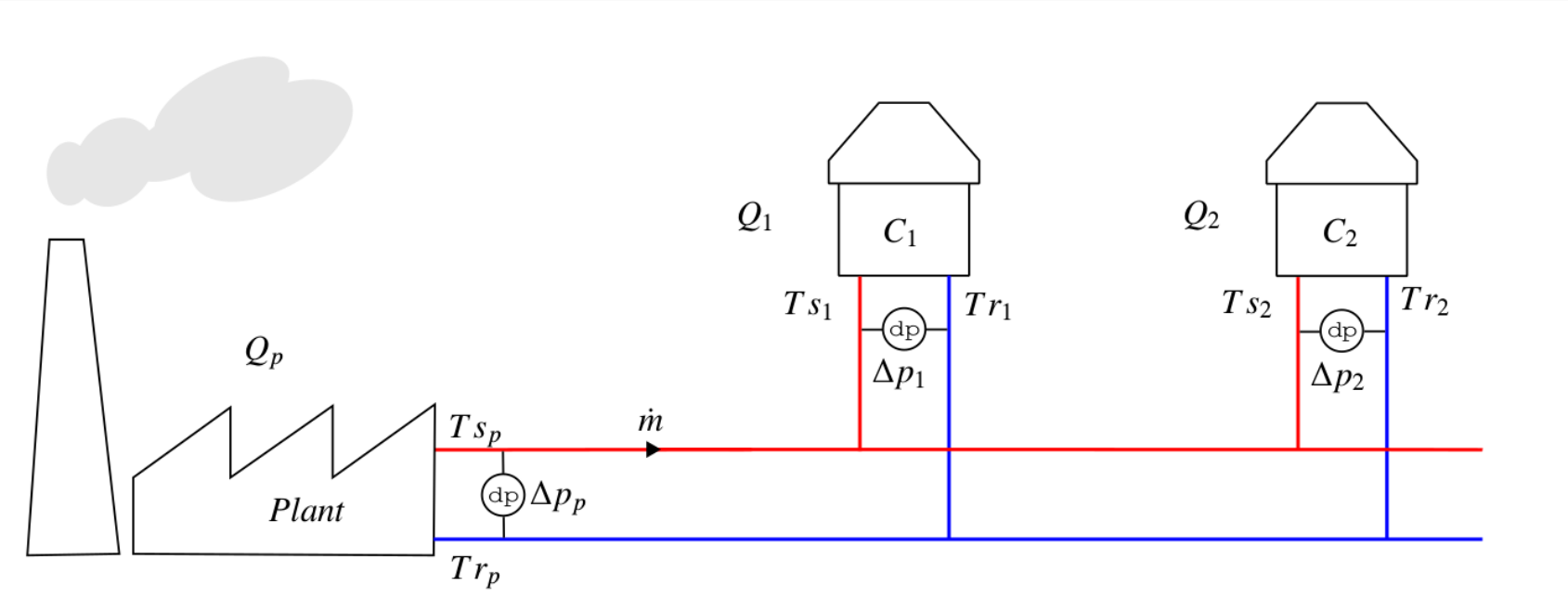


Parsing the title

Online Short-Term Forecast of System Heat Load in District Heating Networks

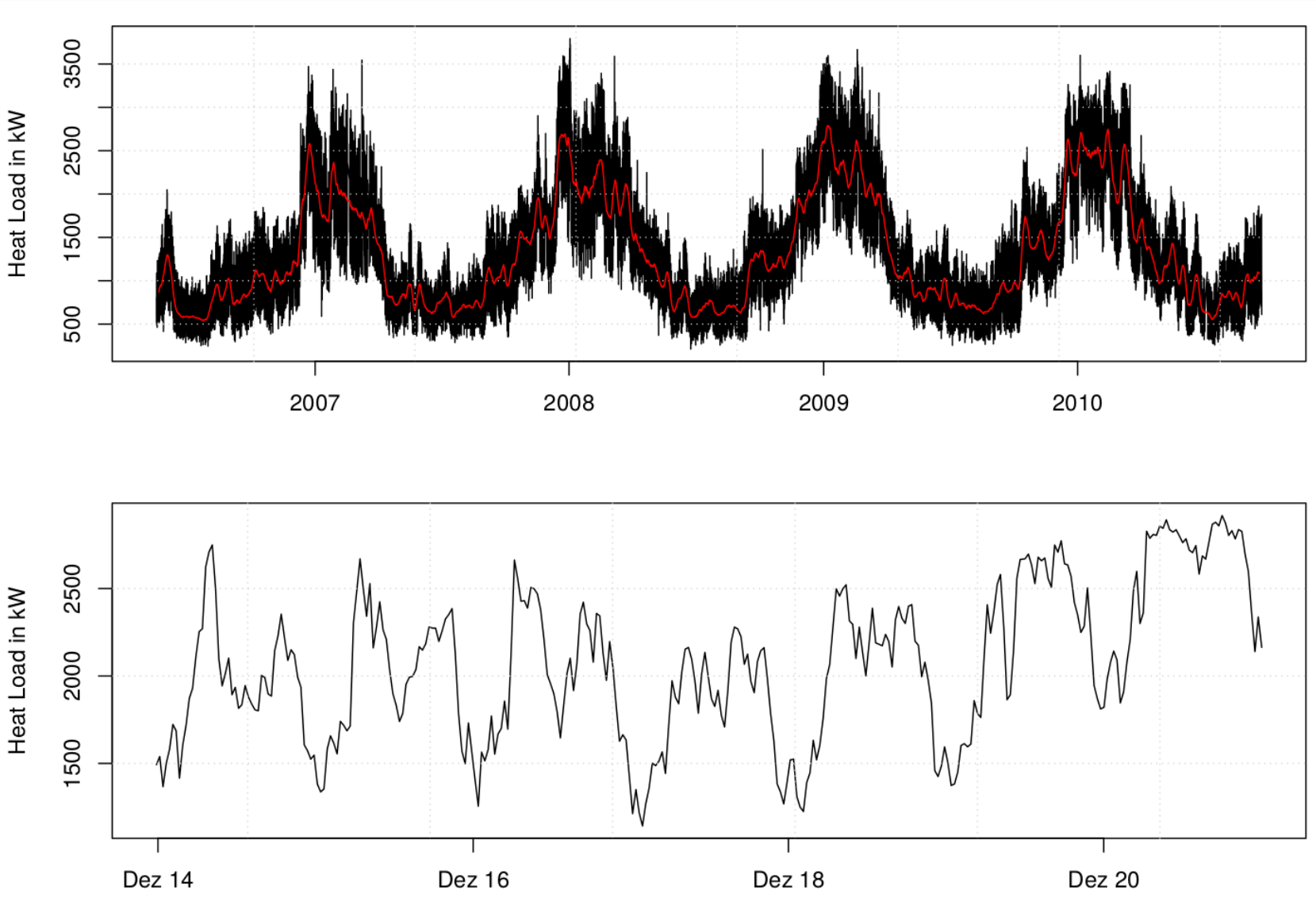
- Variable values are available each step of the model
- 12 – 24h ahead
- Total heat load in central plant
- Central plant distributes heat to network

Material and Methods

Data

- System heat load
- 84 buildings in Tanheim, Austria
- Between 05/18/2006 and 09/22/2010
- 30-minute intervals

Data


Heat Load in kW
500
1500
2500
3500
2007
2008
2009
2010
Heat Load in kW
1500
2000
2500
Dez 14
Dez 16
Dez 18
Dez 20

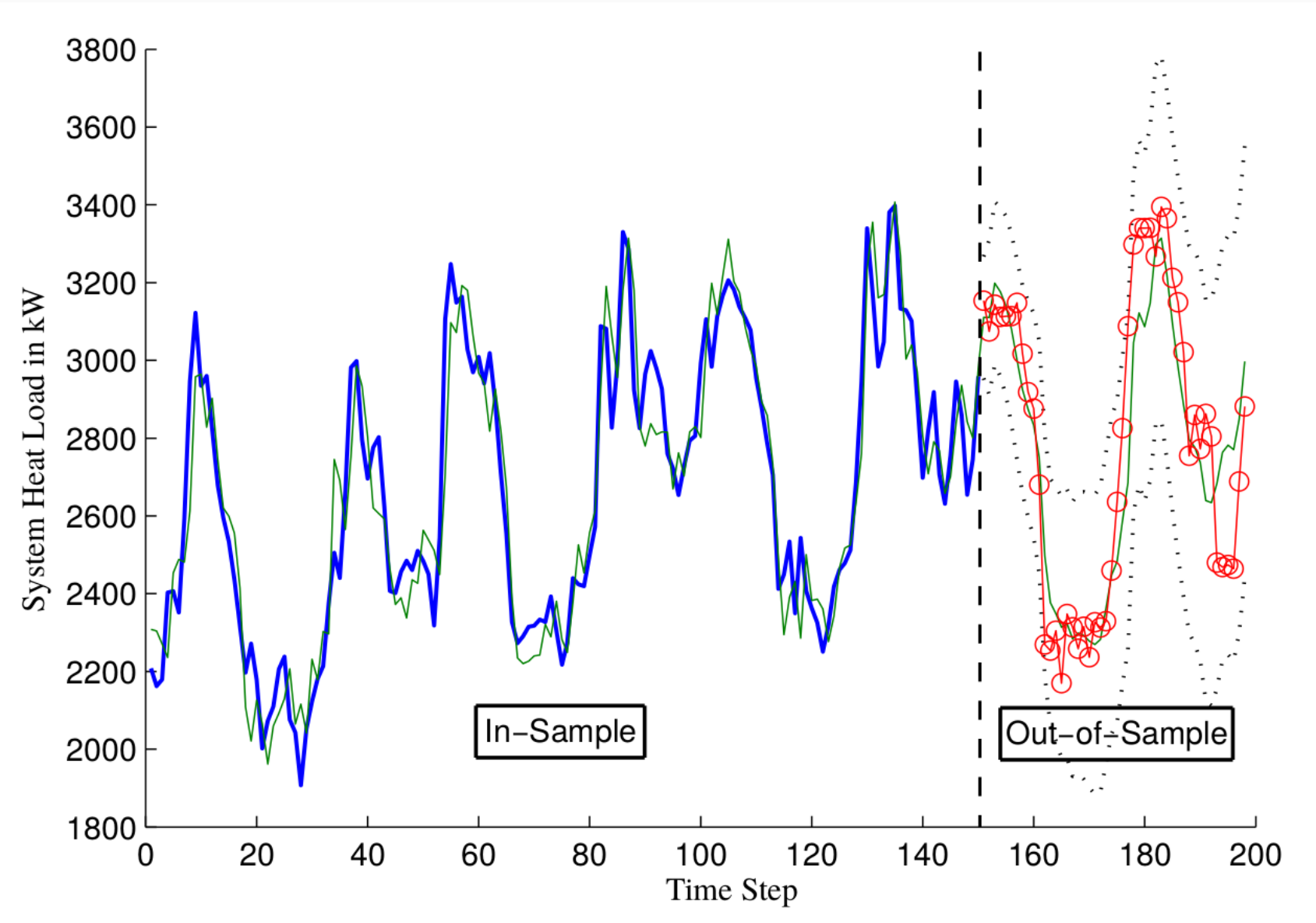
Model

Seasonal AutoRegressive Integrated Moving Average (SARIMA) model

- Time-series
- Repeating patterns – trends
- Short-term correlations
- R and Matlab

Results and Conclusion

Results


System Heat Load in kW
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
0
20
40
60
80
100
120
140
160
180
200
Time Step
In−Sample
Out−of−Sample

Performance

- Accuracy determined by Mean Average Percentage Error (MAPE)
- MAPE calculated over 24 and 48 steps ahead (12h and 24h)
- Predictions compared to real data
- MAPE of 4.4% in one example

Conclusion

Positives

- Results seem (very) good
- Could potentially be used in other networks

Conclusion

Positives

- Results seem (very) good
- Could potentially be used in other networks

Negatives

- Scalability?
- MAPE result only shown for only one example
- More than 24h-ahead predictions?

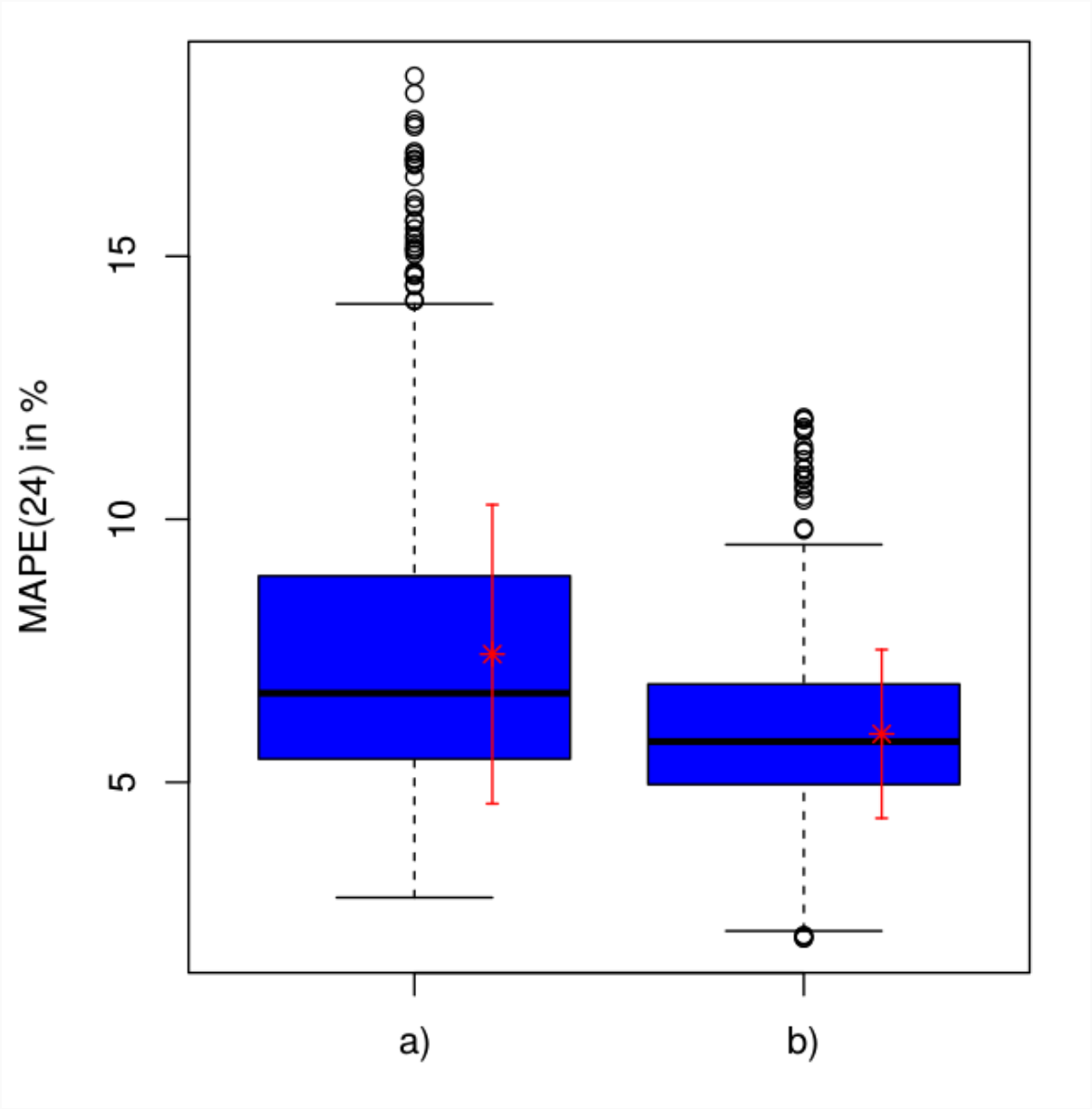
Questions?

SARIMA model

S *Seasonal:* repetitive patterns

AR *AutoRegressive:* variable is regressed on its own lagged values

I *Integrated:* values are replaced with the difference between their values and the previous values

MA *Moving Average:* regression error is a linear combination of previous error terms

MAPE boxplot